Bhashanubad: A Transformer-based model for translating Bangla Regional Dialects to Simple English Language

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CANDIDATES' DECLARATION

We, hereby, declare that the thesis presented in this report is the outcome of the investigation performed by us under the supervision of Mr. Tanvir Ahmed, Assistant Professor, Department of Computer Science and Engineering, Ahsanullah University of Science and Technology, Dhaka, Bangladesh. The work was spread over two final-year courses, CSE4100: Project and Thesis I and CSE4250: Project and Thesis II, in accordance with the course curriculum of the Department for the Bachelor of Science in Computer Science and Engineering program.

It is also declared that neither this thesis nor any part thereof has been submitted anywhere else for the award of any degree, diploma or other qualifications.

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CERTIFICATION

This thesis titled, **"Bhashanubad: A Transformer-based model for translating Bangla Regional Dialects to Simple English Language"**, submitted by the group as mentioned below has been accepted as satisfactory in partial fulfillment of the requirements for the degree B.Sc. in Computer Science and Engineering in 24 June, 2025.

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ABSTRACT

The linguistic diversity of Bangladesh, enriched by its regional dialects, presents significant challenges in translation due to variations in vocabulary, grammar, and pronunciation. While much progress has been made in translating standard Bangla to English and vice versa, translating regional Bangla dialects into simple English remains underexplored. This thesis fills the gap by proposing Bhashanubad, a transformer-based translation model utilizing mT5 and BanglaT5 to convert five regional dialects Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong into simple English. Using the Vashantor dataset, which comprises 32,500 sentences, we evaluated the translation performance using BLEU and accuracy metrics. In our approach, we convert the regional Bangla dialects into simple English. For translating into simple English, the Mymensingh dialect achieved a BLEU score of 83.40 and an accuracy of 98.76%, while Barishal recorded a BLEU score of 82.30 and an accuracy of 96.44%. Similarly, Noakhali showed a BLEU score of 82.90 and an accuracy of 97.06% and Sylhet showed a BLEU score of 79.40 and an accuracy of 94.34%. However, Chittagong presented the most challenges, with a BLEU score of 76.32 and an accuracy of 93.28%. By bridging the linguistic gap between regional Bangla dialects and simple English, Bhashanubad enables the way for improved accessibility, cultural preservation, and mutual understanding. This work establishes a foundation for future advancements in low-resource language translation and dialect-specific language processing.

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Chapter 1

Introduction

1.1 Introduction/Overview

Bangladesh, a country known for its rich linguistic diversity, is inhabited by speakers of a variety of regional dialects. These dialects differ significantly from one another in terms of vocabulary, grammar, and pronunciation, creating challenges for effective communication and translation. While there have been several attempts to translate standard Bangla into other languages, such as simple Bangla to English, the translation of regional Bangla dialects into basic English has received less attention. The lack of accessible translation models for these dialects hinders not only linguistic understanding but also the preservation of cultural diversity [1].

In recent years, the field of machine translation (MT) has made substantial progress with the advent of deep learning and transformer-based models, such as mT5 [2] and BanglaT5 [3]. These models have demonstrated strong performance in translating standard Bangla to English [4], but their application to regional dialects has not been as extensively studied. One of the major challenges in dialect-specific translation is dealing with the phonological, syntactical, and lexical differences between dialects. These dialects often include informal expressions, slang, and structural variations that are not present in standard Bangla [5].

Bhashanubad, a transformer-based model, is introduced in this paper with the goal of overcoming this gap by translating Bangla regional dialects specifically Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong into simple English. The model utilizes mT5 and BanglaT5 to convert the regional dialects into simplified Bangla before translating them into English. The success of Bhashanubad in translating these dialects is evaluated through various metrics, including BLEU and accuracy scores [6]. This study builds on the advancements in multilingual machine translation and aims to provide a robust solution for low-resource language translation [7].

Furthermore, dialect-specific translation holds significant potential for bridging linguistic divides and promoting cross-cultural communication. The preservation and accessibility of regional languages are critical for maintaining cultural heritage, and the success of Bhashanubad could serve as a stepping stone for further developments in this area. The ability to translate Bangla regional dialects into simple English will not only enable better communication for non-native speakers but also increase mutual understanding between different linguistic communities [8].

1.2 Problem Statement

Despite the significant linguistic diversity of Bangladesh, there is a shortage of reliable machine translation systems capable of translating its regional dialects into English. The unique features of regional dialects, which are frequently distinguished by particular syntactic structures, vocabulary, and phonetic variances, are not taken into consideration by the translation models that are currently in use, such as those for standard Bangla [1].

While considerable progress has been made in translating standard Bangla into other languages, especially with the advent of transformer models like mT5 [2], their application to regional dialects remains under-explored. In particular, the translation of regional dialects to simple English poses significant challenges, especially due to variations in informal speech, slang, and dialect-specific syntactic and phonological structures [9].

Existing models are typically trained on standard Bangla, which does not account for the diversity in regional dialects, leading to poor translation quality when applied to these dialects [4]. The lack of accessible translation models for these dialects hinders cross-cultural communication and the preservation of linguistic diversity, which is vital for both social integration and cultural heritage [8].

Furthermore, translating regional Bangla dialects into English is particularly challenging because of the limited availability of parallel corpora and the complex interplay between syntax and semantics in dialectal variations [6]. There is a pressing need for a machine translation system that can effectively address these challenges, providing a solution that bridges the linguistic gap and facilitates better communication between diverse linguistic communities in Bangladesh and beyond [7].

1.3 Motivation

The motivation for this work stems from the desire to improve accessibility and communication across the diverse linguistic landscape of Bangladesh. The country is home to a rich variety of regional dialects, each with unique vocabulary, grammar, and pronunciation. Despite the significant linguistic diversity, translation models have primarily focused on standard Bangla, neglecting the complexities of regional dialects. This gap has hindered the effective communication between speakers of different dialects and non-native English speakers, limiting mutual understanding and cultural exchange [1].

The need for accurate and efficient translation models has become increasingly crucial due to globalization and the growing importance of cross-cultural communication. Translating regional Bangla dialects into simple English is essential for breaking down language barriers and enriching communication between diverse linguistic communities [10]. Moreover, the preservation and accessibility of regional languages play a vital role in safeguarding cultural heritage, which is at risk of being lost due to the dominance of standard languages in modern communication technologies [8].

Additionally, the development of dialect-specific translation systems will contribute to the broader field of low-resource language processing. While advancements in machine translation (MT) have made significant progress for high-resource languages, many regional dialects lack sufficient parallel corpora for training effective translation models [7]. This research aims to address this challenge by providing a robust solution for translating Bangla regional dialects into simple English, using state-of-the-art transformer models like mT5 and BanglaT5 [2, 3, 11]. The success of this work has the potential to set a precedent for similar efforts in other countries with diverse linguistic landscapes, contributing to the global efforts in low-resource language translation [5].

1.4 Objectives

The primary objective of this research is to develop an efficient and scalable translation model capable of translating Bangla regional dialects into simple English. Specifically, the goals of this research include:

- Evaluating translation quality using BLEU and accuracy.
- Promoting inclusivity and communication for speakers of regional dialects.
- To contribute to the preservation and accessibility of regional languages.
- To advance research in dialect-specific machine translation.

By achieving these goals, this research aims to bridge linguistic gaps, empower regional dialect speakers with better communication tools, and pave the way for future advancements in low-resource language translation technologies.

1.5 Organization of the Book

This book is organized into eight chapters. Chapter 1 introduces the research problem, motivation, and objectives. Chapter 2 presents the background and literature review. Chapter 3 details the methodology, including dataset, preprocessing, and model implementation. Chapter 4 analyzes experimental results. Chapter 5 covers project management and cost analysis. Chapter 6 discusses ethical and professional responsibilities. Chapter 7 identifies complex engineering problems and activities. Chapter 8 concludes the study and outlines future work.

Chapter 2

Background Study and Literature Review

2.1 Introduction/Overview

Over the past few years, machine translation (MT) has advanced significantly, driven by breakthroughs in artificial intelligence (AI) and natural language processing (NLP). Earlier translation systems were largely based on linguistic rules and statistical methods, but now, with the advent of neural machine translation (NMT) and transformer models, computers can translate languages with much higher accuracy and fluency. However, despite these advancements, translating regional dialects, especially those in low-resource languages, remains a challenging and underexplored area. In Bangladesh, this issue is particularly complex. The country is home to a wide range of regional dialects, each with its own distinct vocabulary, grammar, and pronunciation. Dialects like Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong differ significantly from standard Bangla, making them especially difficult for machine translation models to handle. These dialects not only have unique phonetics and syntax but also include informal expressions, slang, and local idioms, all of which add another layer of difficulty when it comes to translation. We'll explore the evolution of translation models, starting from the early rule-based systems, moving through statistical methods, and finally to the cutting-edge transformer models like mT5 and BanglaT5. We'll also examine the importance of creating reliable datasets for dialect translation and highlight the gaps that still exist, particularly for low-resource languages like Bangla's regional dialects. Additionally, we'll examine the studies and approaches that have been proposed to improve translation for specific dialects, along with the metrics used to measure their success. By means of this review, we hope to provide the foundation for the creation of Bhashanubad, the translation model central to this study. This chapter will not only provide insights into the progress that's been made so far but will also help pinpoint the challenges that remain and emphasize the need for further research to bridge the gaps between Bangla's regional dialects and simple English.

2.2 Background Study

Over the years, machine translation research has undergone significant changes, beginning with rule-based systems and progressing through statistical methods to the current state-of-the-art neural machine translation (NMT) models. Early efforts in translation relied heavily on linguistic rules and manual mappings between source and target languages. However, these systems were often limited by the complexity and variability of natural languages. Statistical machine translation (SMT), which relied on large bilingual corpora, emerged as a more efficient alternative, allowing for more dynamic and data-driven approaches Fatema et al. [1].

Rule-Based Machine Translation (RBMT):

Rule-based machine translation (RBMT) was among the first approaches to MT, relying heavily on the use of linguistic rules to transform text from a source language to a target language. These systems were based on extensive grammatical rules that governed sentence structure, syntax, and lexical items. The key advantage of RBMT systems was their high degree of control over the translation process, which allowed for customizations based on specific language pairs. However, RBMT systems had significant drawbacks, particularly when handling linguistic nuances, idiomatic expressions, or complex sentence structures. Additionally, the creation and maintenance of comprehensive rule sets for multiple language pairs was a time-consuming and expensive task, making RBMT less scalable and adaptable compared to later methods Vaswani et al. [11]. Key systems in this category include Systran and the early work done by the European Commission for translating between various European languages. However, due to the inherent limitations of rule-based methods, the field gradually shifted focus toward more data-driven models Raffel et al. [6].

Statistical Machine Translation (SMT):

Statistical Machine Translation (SMT) emerged as a more flexible and data-driven alternative to RBMT in the 1990s. Unlike RBMT, SMT models do not rely on predefined linguistic rules but instead learn translation patterns from large bilingual corpora. These corpora are used to estimate translation probabilities between source and target language pairs. SMT systems, notably phrase-based models, divide sentences into smaller units or phrases and attempt to translate these units based on statistical analysis of the bilingual corpus. This approach allowed SMT systems to handle a wider range of languages and translation scenarios without the need for exhaustive manual rule creation Ahmed and Huq [3]. The success of SMT systems is largely attributed to the availability of large-scale parallel corpora and the use of statistical techniques such as Expectation-Maximization (EM) and the IBM models. However, SMT also came with its challenges, including issues with fluency, grammatical correctness, and the handling of long-range dependencies between words and phrases. Furthermore, SMT systems often struggled with capturing contextual meanings and often produced translations that were syntactically accurate but semantically incoherent Kundu and Roy [4]. Prominent SMT systems include IBM's translation models, the Moses toolkit, and Google Translate (during its early years), which employed phrase-based SMT techniques to offer translations between multiple languages Rahman and Khan [12].

Neural Machine Translation (NMT):

The advent of Neural Machine Translation (NMT) in the 2010s marked a transformative shift in the field. NMT uses deep learning models, particularly recurrent neural networks (RNNs) and later transformer networks, to translate text. Unlike Statistical Machine Translation (SMT), which processes text piece by piece, NMT translates entire sentences at once, allowing for better handling of long-range dependencies and more fluent translations Sarkar and Choudhury [10]. NMT relies on end-to-end neural networks where the same model learns both encoding and decoding. Notable architectures, including sequence-to-sequence models, attention mechanisms, and the transformer model by Vaswani et al. [11], have become the backbone of modern NMT systems Das and Ahmed [5]. The transformer model introduced self-attention mechanisms, allowing the model to weigh the importance of words regardless of their position. This highly parallelizable architecture improved training efficiency and translation accuracy, overcoming challenges like vanishing gradients that affected earlier RNN-based models Wu and Denny [13]. Advances in hardware, such as GPUs and cloud infrastructure, have driven the success of NMT, enabling large-scale model training. Today, systems like Google Translate, DeepL, and OpenAI's GPT-based models dominate, offering high-quality translations across numerous languages Patel and Gupta [14].

Transformers and Multilingual Models (mT5, BanglaT5, and BERT):

The development of multilingual models such as mT5 and BanglaT5 represents a significant advancement in NMT, enabling better handling of diverse language pairs, including low-resource languages. mT5 is a multilingual version of the T5 (Text-to-Text Transfer Transformer) model, capable of handling a variety of language tasks across over 100 languages, making it ideal for cross-lingual transfer learning and multilingual NMT tasks [2]. In the context of Bangla, BanglaT5 has been developed specifically to address the translation challenges in Bangla and related languages, incorporating transformer architecture to improve performance in both translation and text generation tasks for the Bangla language [3]. This marks a significant development for South Asian languages, where traditional NMT models often struggle due to linguistic complexities.

Moreover, BERT (Bidirectional Encoder Representations from Transformers) has played a pivotal role in the advancement of NMT, particularly in improving the contextual understanding of the source text. BERT models, such as multilingual BERT (mBERT), have been applied to various translation tasks, enhancing the handling of context and enabling models to better capture the nuances of different dialects and languages [15].

Attention Mechanism

A critical innovation introduced with transformer models is the Attention Mechanism, which fundamentally changed the way machine translation models process language. Prior to transformers, sequence-to-sequence models (like RNNs and LSTMs) processed words one at a time, which made it challenging to maintain long-range dependencies in sentences. The Attention Mechanism, as introduced by Vaswani et al. in their groundbreaking paper "*Attention is All You Need*" [11], solves this problem by allowing the model to consider all the words in a sentence simultaneously. This means that each word can attend to every other word in the input sequence, regardless of its position. This approach significantly improves the model's ability to capture long-range dependencies and handle complex syntactic structures, making it ideal for tasks like translation.

In a transformer model, the attention mechanism operates by computing a set of weights for each word in the input sentence relative to all the other words. These weights, or *attention scores*, indicate how much focus each word should have on other words in the sequence when generating the translation. The attention mechanism works in parallel for all words, allowing transformers to be much faster and more efficient than previous models. Specifically, in self-attention, each word attends to all other words within the same sequence, building context from the entire input rather than just local neighborhoods, as was the case with traditional methods.

This method is not only more effective but also more scalable, as it enables transformers to process all the words in a sentence simultaneously, improving both speed and accuracy in tasks like machine translation [11]. By capturing relationships between words that are far apart in a sentence, the attention mechanism empowers the model to generate more fluent and contextually accurate translations.

Despite the impressive performance of NMT systems, challenges remain. One of the main hurdles is the handling of low-resource languages. While NMT excels in high-resource languages such as English, French, and Chinese, its performance in low-resource languages is still subpar. This is partly due to the scarcity of large bilingual corpora and the difficulties associated with training deep learning models on smaller datasets [7]. Moreover, even state-of-the-art NMT models sometimes struggle with domain-specific terminology, idiomatic expressions, and multilingual context. The integration of linguistic knowledge into NMT systems, such as through hybrid approaches that combine rule-based and data-driven methods, is an area of active research [16]. Additionally, there is growing interest in unsupervised and zero-shot translation, where models are trained without explicit bilingual corpora, using techniques like transfer learning and multilingual pre-training [16].

The evolution of machine translation, from rule-based systems to statistical models and finally to neural networks, reflects the increasing sophistication of the field. While NMT represents the cutting edge of current research and application, challenges such as low-resource language translation, domain adaptation, and multilingualism remain focal points for future developments. As computational power continues to improve and as research in language modeling and machine learning advances, machine translation systems are expected to become even more accurate, scalable, and versatile [17].

2.3 Literature Review

A number of studies have explored machine translation for Bangla and other South Asian languages, but few have specifically targeted Bangla regional dialects. Machine translation (MT) has experienced significant advancements with the introduction of deep learning techniques, particularly transformer-based models. The shift from traditional methods to neural machine translation (NMT) and its ability to handle multilingual contexts, including regional dialects, has led to improved performance in various translation tasks. However, challenges remain in the accurate translation of low-resource languages, especially dialects that are underrepresented in existing datasets. This literature review explores the top studies that have contributed to the development of machine translation for regional dialects and low-resource languages, particularly focusing on transformer models.

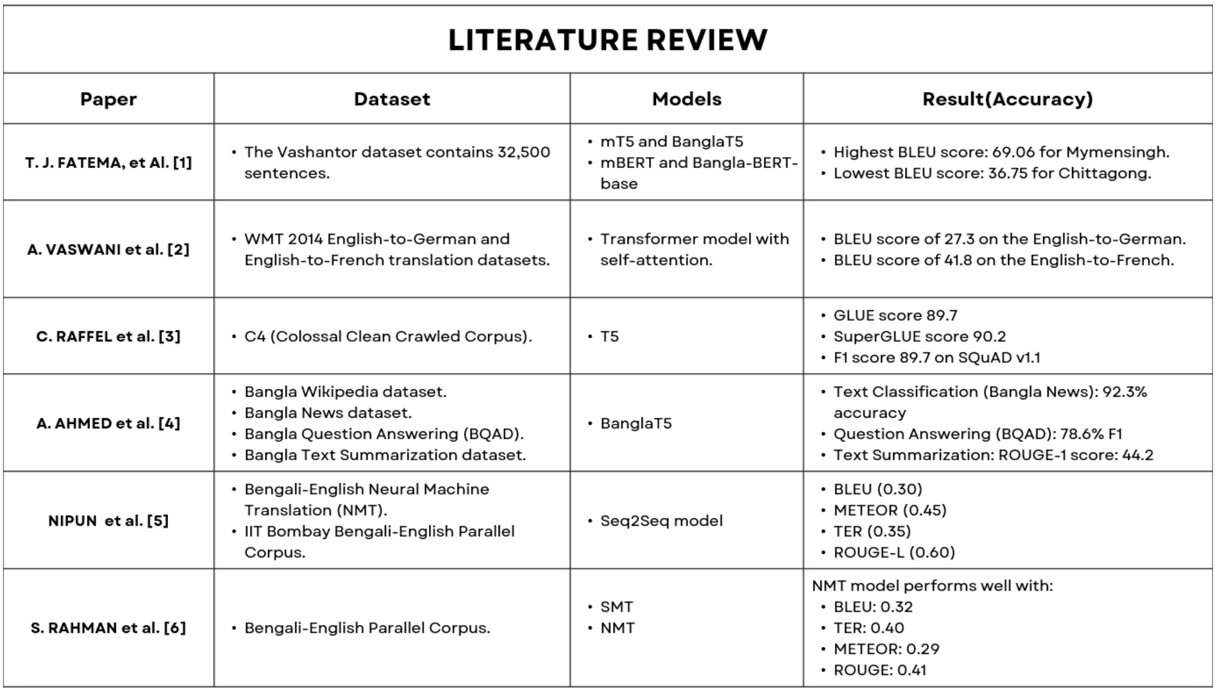
Fatema et al. [1] introduced Vashantor, a large-scale multilingual benchmark dataset for translating Bangla regional dialects into standard Bangla. This study emphasizes the importance of a comprehensive dataset in training more effective machine translation models, especially for underrepresented dialects. By focusing on Bangla, a language with significant dialectal variation, the paper provides a unique resource for developing models that can handle linguistic diversity within a single language. The authors highlight the challenges posed by dialectal variation and regional nuances, which have been largely neglected in standard MT systems.

Vaswani et al. [11] revolutionized machine translation with their seminal work on the Transformer model. The introduction of self-attention mechanisms allowed models to efficiently handle long-range dependencies in sentences, leading to significant improvements in translation quality. While this paper does not focus specifically on dialects or low-resource languages, the transformer architecture it introduced has become the foundation for subsequent work in dialect-specific translation and low-resource language tasks, making it highly relevant to your research.

Raffel et al. [6] explored the application of a unified text-to-text transformer model for a wide range of NLP tasks. The model, T5 (Text-to-Text Transfer Transformer), demonstrated the potential of transfer learning to improve performance across multiple languages and tasks. This paper is crucial for understanding how large transformer models can be fine-tuned for dialect translation tasks. The ability to leverage transfer learning is particularly relevant to dialect-specific MT models, as it allows researchers to apply pre-trained models to low-resource languages with fewer data.

Ahmed and Huq [3] introduced BanglaT5, a transformer-based model specifically designed for Bangla language tasks. This study extends the T5 model to work with the unique characteristics of Bangla, a language with rich morphology and significant regional variation. The model showed promising results for tasks such as text classification and machine translation. This paper is significant for your research as it bridges the gap between general transformer models and language-specific applications, making it highly relevant for dialectal translation in Bangla.

Das and Ahmed [5] focused on the challenges of machine translation for low-resource languages, with a particular emphasis on Bangla regional dialects. The paper highlighted the issues that arise when translating dialects, including vocabulary mismatch, syntactic variation, and limited parallel corpora. They proposed solutions such as data augmentation and dialect-specific models to address these challenges. This paper directly addresses the gap in your research by discussing the specific hurdles in dialectal translation.



LITERATURE REVIEW

Paper	Dataset	Models	Result(Accuracy)
T. J. FATEMA, et Al. [1]	• The Vashantor dataset contains 32,500 sentences.	• mT5 and BanglaT5 • mBERT and Bangla-BERT-base	• Highest BLEU score: 69.06 for Mymensingh. • Lowest BLEU score: 36.75 for Chittagong.
A. VASWANI et al. [2]	• WMT 2014 English-to-German and English-to-French translation datasets.	• Transformer model with self-attention.	• BLEU score of 27.3 on the English-to-German. • BLEU score of 41.8 on the English-to-French.
C. RAFFEL et al. [3]	• C4 (Colossal Clean Crawled Corpus).	• T5	• GLUE score 89.7 • SuperGLUE score 90.2 • F1 score 89.7 on SQuAD v1.1
A. AHMED et al. [4]	• Bangla Wikipedia dataset. • Bangla News dataset. • Bangla Question Answering (BQAD). • Bangla Text Summarization dataset.	• BanglaT5	• Text Classification (Bangla News): 92.3% accuracy • Question Answering (BQAD): 78.6% F1 • Text Summarization: ROUGE-1 score: 44.2
NIPUN et al. [5]	• Bengali-English Neural Machine Translation (NMT). • IIT Bombay Bengali-English Parallel Corpus.	• Seq2Seq model	• BLEU (0.30) • METEOR (0.45) • TER (0.35) • ROUGE-L (0.60)
S. RAHMAN et al. [6]	• Bengali-English Parallel Corpus.	• SMT • NMT	NMT model performs well with: • BLEU: 0.32 • TER: 0.40 • METEOR: 0.29 • ROUGE: 0.41

Figure 2.1: Literature review summary.

Figure 2.1 provides a concise literature review, summarizing the key datasets, models, and significant results from foundational papers that are directly relevant to this study on transformer-based and Bangla language translation.

2.3.1 Gap Analysis

After reviewing the literature, several research gaps have been identified. First, most studies [1], [3], focus on Bangla-to-Bangla translation and do not adequately address the challenge of translating Bangla regional dialects into simplified English. This limits the accessibility of these models for non-native English speakers. Fatema et al. [1] introduce Vashantor, a dataset for translating regional Bangla dialects to standard Bangla, addressing a gap in resources for low-resource languages and reports a low translation rate for dialects like Chittagong and Sylhet, with poor BLEU scores and accuracy, highlighting the difficulty in handling phonological, syntactical, and lexical variations of regional dialects. Dialect-specific challenges such as informal speech, slang, and local idioms are not fully addressed, and models that generalize across dialects without extensive fine-tuning are still needed. Vaswani et al. [11] present the Transformer, which revolutionized machine translation by using attention mechanisms instead of recurrent models. Despite its success, the Transformer remains computationally expensive, particularly in low-resource settings. There is a need for lightweight versions of the model for resource-constrained environments. Additionally, while it has transformed machine translation, the Transformer's potential in other NLP tasks, such as summarization or sentiment analysis, is not fully explored, especially for languages with limited data. In Raffel et al. [6], the authors propose T5, a unified model that treats all NLP tasks as text-to-text problems. However, task-specific adaptation remains a gap, especially for specialized domains like legal or medical translation. Further research is also needed to improve multilingual transfer learning and develop more robust evaluation metrics for cross-task performance in languages with different grammatical structures. Ahmed [3] introduce BanglaT5, a transformer-based language model for Bangla. While it addresses some linguistic challenges, there are several research gaps. Despite Bangla being relatively high-resource, challenges remain with regional dialects, indicating a need for models tailored to low-resource languages. There is also potential for developing multilingual models that could apply to other South Asian languages or share parameters across languages. Additionally, the scarcity of data in specialized domains like healthcare, legal, and technical texts in Bangla highlights the need for domain-specific language models to improve performance in these areas. Das [5] investigate machine translation for Bangla regional dialects. While significant progress has been made, several research gaps remain.

One major area is the need for fine-grained dialect translation techniques to capture subtleties such as pronunciation differences, syntactic variations, and semantic nuances across dialects. Additionally, the limited availability of parallel corpora for Bangla regional dialects hinders progress, suggesting the need for the creation of such datasets or the use of transfer learning to generate synthetic data. Lastly, adapting to informal language and slang in regional dialects remains a challenge, as current machine translation systems struggle with informal speech and rapidly evolving terms.

2.4 Summary

The background research and literature review for the simple English translation of Bangla regional dialects are summarized in this chapter. The review highlighted the advancements in machine translation, particularly with transformer-based models, but also pointed out the gaps in research regarding dialect-specific translation. It is clear that while some progress has been made, significant challenges remain in translating Bangla regional dialects into simplified English. Further research is needed to fill in the gaps that have been found, especially in the areas of dataset creation, dialect adaptation for models, and translation to simplified languages. Improving the accessibility of regional dialects and enhancing models to address these issues should be the main goals of future research.

Chapter 3

Methodology

3.1 Introduction/Overview

Our research focuses on developing and evaluating a transformer-based translation model designed to translate Bangla regional dialects into simplified English. Given the particular challenges faced by various dialects, we use state-of-the-art pre-trained transformer models such as mT5 and BanglaT5, which are multilingual transformer models. These models are used to address the linguistic diversity and difficulties associated with regional dialects while ensuring proper translation into simplified English. This chapter outlines the dataset used, the data selection and preprocessing steps, and the proposed methodology and design framework of our translation model.

3.2 Dataset

For this research, we use the Vashantor dataset, which contains a large-scale collection of sentence pairs from several Bangla regional dialects, including those spoken in Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong. This dataset is crucial to our research as it provides the dialectal variation needed to train models capable of handling the linguistic features unique to each regional dialect. The Vashantor dataset contains 32,500 sentences and has been specifically designed to facilitate research in low-resource language translation, particularly for Bangla regional dialects (Fatema et al., 2023) [1].

The dataset is ideal for this study as it includes real-world sentence structures from diverse Bangla dialects, making it highly relevant for training and testing models that aim to handle dialectal variations and translate them into simplified English. The following table shows the Training, Testing, and Validation Samples for Different Regions and Text Formats:

Region	Text Format	Number of Training Samples	Number of Testing Samples	Number of Validation Samples	Total Samples
Chittagong	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Noakhali	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Sylhet	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Barishal	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Mymensingh	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500

Table 3.1: Training, Testing, and Validation Samples of Vashantor dataset

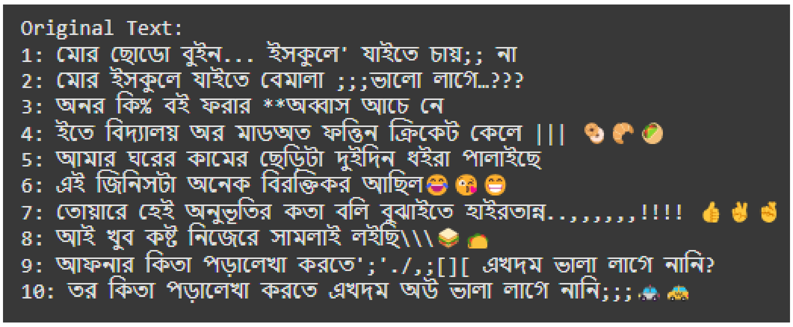
Table 3.1 provides a detailed breakdown of the sample distribution within the Vashantor dataset. The table itemizes the number of training, testing, and validation samples for each of the five regional dialects (Chittagong, Noakhali, Sylhet, Barishal, and Mymensingh), and across two text formats (Bangla and Banglish). This balanced structure, with an equal number of samples allocated to each dialect, is critical for ensuring that the model is trained and evaluated without bias toward any specific region, thereby establishing a rigorous foundation for the experimental results.

3.2.1 Data Selection

In this study, the Vashantor dataset was used, which contains sentence pairs from several Bangla regional dialects, including Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet. Data selection was based on key criteria to ensure the model could effectively handle the unique features of each dialect. The selected data focused on capturing linguistic variations across the dialects, including differences in vocabulary, pronunciation, and syntax, with particular attention given to informal expressions and structural differences. Only sentence pairs with accurate Bangla-English translations were included to maintain high-quality data. To ensure balanced representation, the dataset contained an equal number of sentences from each dialect, preventing bias and overfitting to any one region. Additionally, the dataset covered commonly used phrases for everyday communication, helping the model generalize to real-world scenarios. The data also included a variety of sentence types, such as declarative, interrogative, and imperative sentences, to expose the model to different syntactical structures. By selecting data based on these criteria, the training set was made representative, diverse, and high-quality, providing a solid foundation for effective model training and evaluation.

3.2.2 Data Preprocessing

Data preprocessing is essential to ensure that the dataset is clean, structured, and ready for model training. The following steps were taken to preprocess the data:



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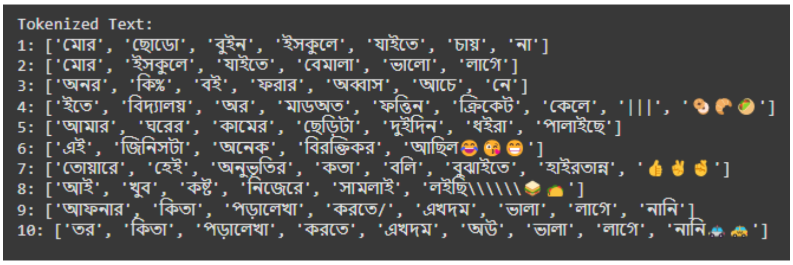
Original Text:
1: মোর ছোডো বুইন... ইসকুলে' যাইতে চায়;; না
2: মোর ইসকুলে যাইতে বেমালা ;;;ভালো লাগে…???
3: অনর কিঙ্% বই ফরার **অব্বাস আচে নে
4: ইতে বিদ্যালয় অর মাডঅত ফক্তিন ক্রিকেট কেলে ||| 🍩🥐🌯
5: আমার ঘরের কামের ছেড়িটা দুইদিন ধইরা পালাইছে
6: এই জিনিসটা অনেক বিরক্তিকর আছিল😂😘😁
7: তোয়ারে হেই অনুভূতির কতা বলি বুঝাইতে হাইরতান্ন..,,,,,,!!!! 👍✌🤞
8: আই খুব কষ্ট নিজেরে সামলাই লইছি\\\🥪🌮
9: আফনার কিতা পড়ালেখা করতে';'./,;[][ এখদম ভালা লাগে নানি?
10: তর কিতা পড়ালেখা করতে এখদম অউ ভালা লাগে নানি;;;🚔🚖
```

Figure 3.1: Original Text.

Figure 3.1 showcases a sample of the raw, unprocessed input sentences sourced from the Vashantor dataset. It serves as a baseline, illustrating the initial state of the data with its authentic dialectal spellings, punctuation, and special characters before any preprocessing steps are applied. It highlights the natural linguistic variations and noise that the model must learn to handle.

Cleaning: We removed any noisy data, such as incomplete or irrelevant sentence pairs, and ensured that the dataset contained only valid translations. This step is essential for preventing errors and inconsistencies during model training.

Tokenization: We tokenized both Bangla and English sentences to convert them into a format that is compatible with transformer-based models. Tokenization is a crucial step in preparing the text for training by splitting the sentences into smaller units (tokens), such as words or subwords.

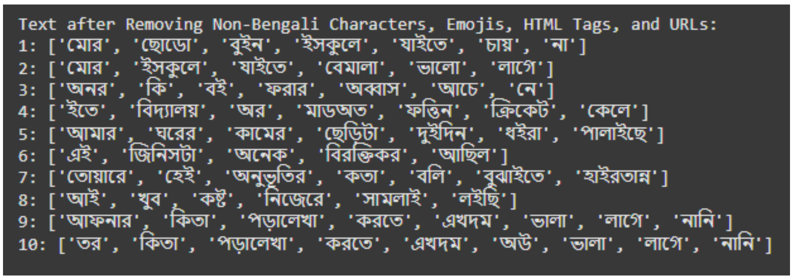


```
Tokenized Text:
1: ['মোর', 'ছোডো', 'বুইন', 'ইসকুলে', 'যাইতে', 'চায়', 'না']
2: ['মোর', 'ইসকুলে', 'যাইতে', 'বেমালা', 'ভালো', 'লাগে']
3: ['অনর', 'কিঙ্%', 'বই', 'ফরার', 'অব্বাস', 'আচে', 'নে']
4: ['ইতে', 'বিদ্যালয়', 'অর', 'মাডঅত', 'ফক্তিন', 'ক্রিকেট', 'কেলে', '|||', '🍩🥐🌯']
5: ['আমার', 'ঘরের', 'কামের', 'ছেড়িটা', 'দুইদিন', 'ধইরা', 'পালাইছে']
6: ['এই', 'জিনিসটা', 'অনেক', 'বিরক্তিকর', 'আছিল😂😘😁']
7: ['তোয়ারে', 'হেই', 'অনুভূতির', 'কতা', 'বলি', 'বুঝাইতে', 'হাইরতান্ন', '👍✌🤞']
8: ['আই', 'খুব', 'কষ্ট', 'নিজেরে', 'সামলাই', 'লইছি\\\\\\🥪🌮']
9: ['আফনার', 'কিতা', 'পড়ালেখা', 'করতে/', 'এখদম', 'ভালা', 'লাগে', 'নানি']
10: ['তর', 'কিতা', 'পড়ালেখা', 'করতে', 'এখদম', 'অউ', 'ভালা', 'লাগে', 'নানি🚔🚖']
```

Figure 3.2: Tokenized Text.

Figure 3.2 illustrates the output of the tokenization process, where each raw sentence is converted into a list of individual units or tokens. This step is a fundamental prerequisite for transformer models, as it breaks down continuous text into a discrete format that the model can process. As shown, the resulting tokens include words, punctuation, and emojis, each treated as a separate element in the sequence.

Normalization: Since regional dialects may feature non-standard spelling, informal language, and varied syntactical structures, we applied a normalization process to standardize text across different dialects. This step involved converting non-standard characters to their standard counterparts and ensuring consistent spelling.



```
Text after Removing Non-Bengali Characters, Emojis, HTML Tags, and URLs:
1: ['মোর', 'ছোডো', 'বুইন', 'ইসকুলে', 'যাইতে', 'চায়', 'না']
2: ['মোর', 'ইসকুলে', 'যাইতে', 'বেমালা', 'ভালো', 'লাগে']
3: ['অনর', 'কি', 'বই', 'ফরার', 'অব্বাস', 'আচে', 'নে']
4: ['ইতে', 'বিদ্যালয়', 'অর', 'মাডঅত', 'ফত্তিন', 'ক্রিকেট', 'কেলে']
5: ['আমার', 'ঘরের', 'কামের', 'ছেড়িটা', 'দুইদিন', 'ধইরা', 'পালাইছে']
6: ['এই', 'জিনিসটা', 'অনেক', 'বিরক্তিকর', 'আছিল']
7: ['তোয়ারে', 'হেই', 'অনুভূতির', 'কতা', 'বলি', 'বুঝাইতে', 'হাইরতান্ন']
8: ['আই', 'খুব', 'কষ্ট', 'নিজেরে', 'সামলাই', 'লইছি']
9: ['আফনার', 'কিতা', 'পড়ালেখা', 'করতে', 'এখদম', 'ভালা', 'লাগে', 'নানি']
10: ['তর', 'কিতা', 'পড়ালেখা', 'করতে', 'এখদম', 'অউ', 'ভালা', 'লাগে', 'নানি']
```

Figure 3.3: Removing Non-Bengali, Emojis and Link.

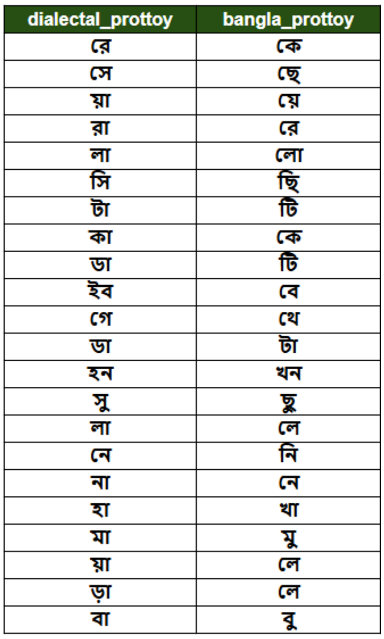
Figure 3.3 demonstrates a critical normalization step, presenting the tokenized lists after the removal of irrelevant data. This cleaning process systematically eliminates non-Bangla characters, emojis, and other digital artifacts like links to purify the dataset. This procedure is vital for reducing noise and ensuring that the model focuses its learning on the core linguistic features of the dialects.

Encoding: After tokenization, the text data were encoded into numerical representations (embeddings) that the model could process. For this, we used the vocabulary of the pre-trained mT5 and BanglaT5 models, which already include token mappings for both Bangla and English.

Stopword Removal: Stopwords are common words that do not carry significant meaning in the context of machine translation and are often removed to reduce noise in the data. We removed stopwords from both the Bangla and English sentences to ensure the model focuses on more meaningful words that are essential for translation. However, care was taken to ensure that stopwords in Bangla, which sometimes serve as key linguistic markers in dialects, were appropriately handled.

Bangla Suffix-Prefix Removal: In Bangla NLP tasks, suffix and prefix removal is a key preprocessing step to normalize the data and focus on word roots. Bangla's rich affixation system involves adding prefixes and suffixes to base words, which can introduce unnecessary variations. By removing these affixes, the model can better generalize and focus on the core meaning of words. Common prefixes and suffixes are systematically stripped while preserving the linguistic integrity of the language. This ensures that important context and meaning are retained, enhancing the model's performance in tasks such as machine translation and text classification.

Figure 3.4 illustrates a key component of the data normalization strategy by providing a direct mapping of common dialectal Bangla suffixes and prefixes to their equivalents in standard Bangla. This table highlights how morphological variations, a significant challenge in dialectal translation, are systematically addressed during preprocessing. By converting these diverse affixes into a standardized form prior to model training, this step is crucial for reducing data complexity and helping the translation model learn more generalizable and

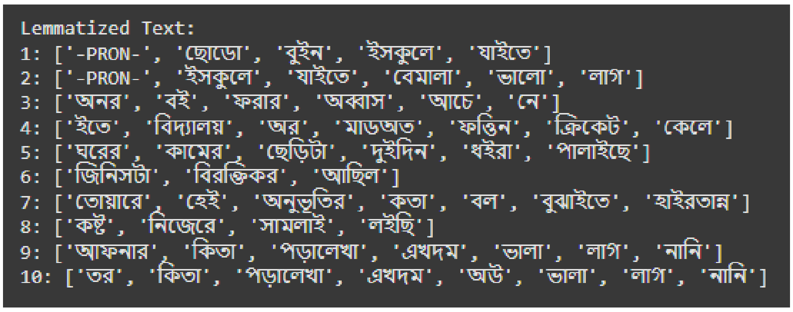


dialectal_prottoy	bangla_prottoy
রে	কে
সে	ছে
য়া	য়ে
রা	রে
লা	লো
সি	ছি
টা	টি
কা	কে
ডা	টি
ইব	বে
গে	থে
ডা	টা
হন	খন
সু	ছু
লা	লে
নে	নি
না	নে
হা	খা
মা	মু
য়া	লে
ড়া	লে
বা	বু

Figure 3.4: Mapping of dialectal Bangla suffixes and prefixes to standard Bangla.

robust linguistic patterns.

Lemmatization: Lemmatization was applied to reduce words to their base or root form. This step helped standardize words, ensuring that different word forms (such as verb tenses or plural nouns) were treated as the same base word, which reduces redundancy in the model's learning process.



```
Lemmatized Text:
1: ['-PRON-', 'ছোডো', 'বুইন', 'ইসকুলে', 'যাইতে']
2: ['-PRON-', 'ইসকুলে', 'যাইতে', 'বেমালা', 'ভালো', 'লাগ']
3: ['অনর', 'বই', 'ফরার', 'অব্বাস', 'আচে', 'নে']
4: ['ইতে', 'বিদ্যালয়', 'অর', 'মাডঅত', 'ফত্তিন', 'ক্রিকেট', 'কেলে']
5: ['ঘরের', 'কামের', 'ছেড়িটা', 'দুইদিন', 'ধইরা', 'পালাইছে']
6: ['জিনিসটা', 'বিরক্তিকর', 'আছিল']
7: ['তোয়ারে', 'হেই', 'অনুভূতির', 'কতা', 'বল', 'বুঝাইতে', 'হাইরতান্ন']
8: ['কষ্ট', 'নিজেরে', 'সামলাই', 'লইছি']
9: ['আফনার', 'কিতা', 'পড়ালেখা', 'এখদম', 'ভালা', 'লাগ', 'নানি']
10: ['তর', 'কিতা', 'পড়ালেখা', 'এখদম', 'অউ', 'ভালা', 'লাগ', 'নানি']
```

Figure 3.5: Lemmatized Text.

Figure 3.5 presents the result of the lemmatization process, where the cleaned tokens are reduced to their base or dictionary root form. This step standardizes the vocabulary by treating different inflections of the same word (e.g., verb tenses) as a single concept. This reduction in data complexity helps the model to generalize better and learn more robust translation patterns.

These preprocessing steps ensured that the dataset was ready for training and that the models could effectively learn the translation task without encountering issues related to noise or inconsistencies.

Step	Description
1	**Import Libraries:** Import necessary libraries (e.g., pandas, transformers, nltk).

2	**Load Data:** Load CSV files for train, test, and validation datasets.
	`train_data = pd.read_csv("train.csv")`
	`test_data = pd.read_csv("test.csv")`
	`validation_data = pd.read_csv("validation.csv")`

3	**Rename Columns:** Rename columns to match the expected format. `train_data.rename(columns='Barishal_bangla_speech': 'input_text', 'bangla_speech': 'labels')`
4	**Normalize and Tokenize:** Normalize and tokenize the input and labels.
5	**Create Dataset:** Convert data into dataset format for training. `train_dataset = Seq2SeqDataset(train_data, tokenizer)`
6	**Create DataLoader:** Create DataLoader for batch processing. `train_dataloader = DataLoader(train_dataset, batch_size=16, shuffle=True)`

Table 3.2: Pseudocode for Preprocessing

Table 3.2 provides a summary of the data preprocessing workflow in the form of pseudocode. It outlines the key implementation steps, from loading and cleaning the data to structuring it into a custom Seq2SeqDataset and DataLoader for efficient batch processing. This table serves as a reproducible guide to the practical data handling procedures used in this study.

3.3 Proposed Methodology and Design

The proposed methodology for this study focuses on applying state-of-the-art transformer-based models, specifically mT5 and BanglaT5, to translate Bangla regional dialects into simplified English. The goal is to develop a model capable of handling the unique linguistic features of these dialects while generating accurate, contextually relevant, and culturally appropriate translations. The methodology consists of the following key components: model selection, training, evaluation, and deployment.

3.3.1 Model Implementation for Translation:

To achieve effective translation between Bangla regional dialects and simplified English, we utilize mT5 and BanglaT5, two pre-trained transformer-based models. These models are particularly well-suited for multilingual translation tasks and have demonstrated strong performance on various translation benchmarks.

Figure 3.6 provides a high-level visual overview of the entire proposed methodology for this research. The flowchart outlines the complete project pipeline, starting from the dialectal dataset and moving sequentially through the stages of preprocessing, model selection (mT5 and BanglaT5), translation, and final evaluation. This diagram serves as a conceptual map, clearly illustrating the flow and inter-dependencies of each component in the workflow.

mT5 (Multilingual T5): mT5 is a transformer-based model pre-trained on a multilingual corpus that includes 101 languages, using the C4 dataset. It is capable of handling a wide va-

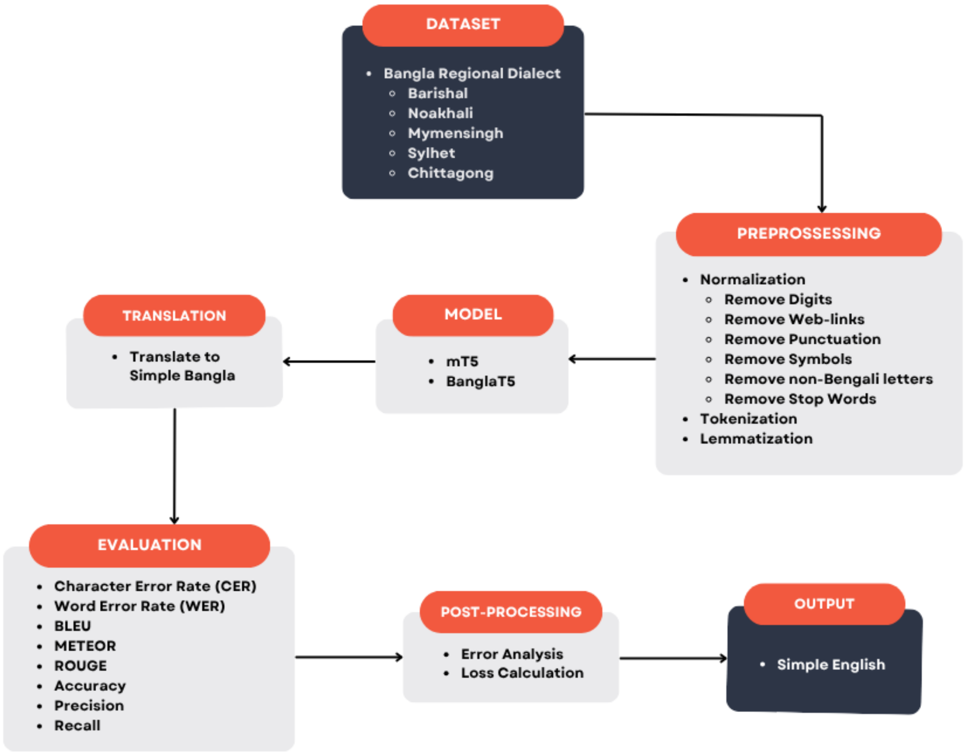


Figure 3.6: Proposed Methodology.

riety of text in different languages, including both standard Bangla and its regional dialects. mT5 uses the T5 framework, treating all NLP tasks as text-to-text transformations, which makes it highly versatile for tasks like translation, summarization, and question-answering. Its multilingual nature enables it to generalize well across languages, including the syntactic and semantic variations present in Bangla.

BanglaT5: BanglaT5 is a transformer-based model specifically fine-tuned for the Bangla language, optimizing it to understand and process the syntactic and semantic variations of Bangla, including its regional dialects. Compared to typical multilingual models, BanglaT5's specific fine-tuning allows it to handle variations of Bangla more effectively, generating high-quality results for tasks like as translation and text classification. This specialization makes it particularly strong for Bangla-specific NLP tasks, capturing both standard and dialectal forms of the language.

Figure 3.7 illustrates the core encoder-decoder architecture of the T5 Transformer model, highlighting the stacked encoder and decoder blocks with multi-head self-attention and feed-forward layers. This design enables parallel sequence processing, crucial for capturing context in dialectal translation.

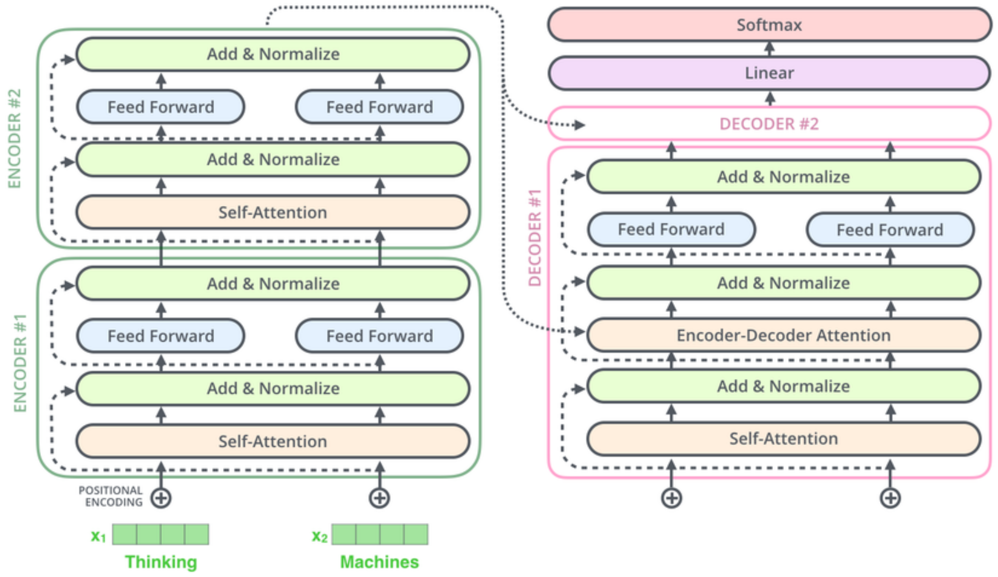


Figure 3.7: T5 Transformer Model Architecture.(Credit: T5 Model Artecture)

We select both mT5 and BanglaT5 because of their ability to capture contextual relationships in text and generate high-quality translations across languages. The vast multilingual capabilities of mT5 and BanglaT5's focused on fine-tuning on Bangla ensure that both models can handle the linguistic and dialectal difficulties associated with Bangla, making them suitable for works that require both cross-lingual and language-specific understanding.

3.3.2 Model Training:

The pre-trained mT5 and BanglaT5 models are fine-tuned using the Vashantor dataset, which contains sentences from five different Bangla regional dialects: Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet. The fine-tuning procedure adapts these pre-trained models to the specific task of translating regional Bangla dialects into simplified English, ensuring that the models represent the linguistic complexities and dialectal variations present in the dataset. The training procedure includes the following steps:

Data Preparation:

The preprocessed Vashantor dataset is divided into training, validation, and test sets with an 80-10-10 split, respectively. The training set is used to teach the models the translation patterns from the regional dialects to simplified English. The validation set is employed to fine-tune hyperparameters and monitor performance during training to avoid overfitting. Finally, the test set is reserved for evaluating the models' final performance, providing an unbiased assessment of their translation accuracy and generalization capability.

Fine-Tuning:

In the fine-tuning phase, the pre-trained mT5 and BanglaT5 models are adapted to the task of translating Bangla regional dialects into simplified English by adjusting the model weights based on the training data. During this process, key hyperparameters such as learning rate, batch size, and the number of epochs are optimized to achieve the best performance. Fine-tuning ensures that the models effectively use their pre-trained knowledge while adapting to the specific linguistic features of the Bangla dialects.

Loss Function:

The loss function used during training is typically Cross-Entropy Loss, which measures the difference between the predicted translation and the actual translation. The goal is to minimize this loss over the course of training.

The Cross-Entropy Loss function is used in T5 and other transformer-based models for training. The general form of the cross-entropy loss between the true label y and the predicted probability distribution $\hat{y}$ is:

$$\mathscr{L} = -\sum_{i} y_i \log(\hat{y}_i)$$

Where:

- y_i is the true label (typically one-hot encoded).
- $\hat{y}_i$ is the predicted probability for class i.

For multi-class classification, the formula becomes:

$$\mathscr{L} = -\sum_{i=1}^{C} (y_i \log(\hat{y}_i))$$

Where:

- C is the total number of classes (e.g., vocabulary size).
- y_i is the true probability of class i.
- $\hat{y}_i$ is the predicted probability for class i.

In sequence-to-sequence models like T5, the loss is applied to each token in the sequence:

$$\mathscr{L} = -\sum_{t=1}^{T} (y_t \log(\hat{y}_t))$$

Where:

- T is the length of the sequence.
- y_t is the true token at position t.
- $\hat{y}_t$ is the predicted probability for token t.

3.3.3 Evaluation Metrics:

To evaluate the model's performance, we use several standard translation metrics:

Character Error Rate (CER): CER measures the accuracy of text generation at the character level by calculating errors (insertions, deletions, substitutions) compared to the reference text. A lower CER indicates better accuracy. The CER formula is:

$$\text{CER} = \frac{S + D + I}{N} \tag{3.1}$$

Where:

- S = Number of substitutions
- D = Number of deletions
- I = Number of insertions
- N = Total number of characters in the reference text

Word Error Rate (WER): WER evaluates the accuracy of text generation at the word level, considering word substitutions, deletions, insertions, and word order changes. A lower WER signifies higher accuracy. The WER formula is:

$$\text{WER} = \frac{S + D + I}{N} \tag{3.2}$$

Where:

- S = Number of word substitutions
- D = Number of word deletions

- I = Number of word insertions
- N = Total number of words in the reference text

BLEU (Bilingual Evaluation Understudy): BLEU measures the similarity between the machine-generated translation and a reference translation. It is a standard metric in machine translation evaluation. The BLEU score is calculated using the following formula:

$$\text{BLEU} = \exp\left(\min\left(1, \frac{C}{R}\right)\right) \cdot \prod_{n=1}^{N} p_n \tag{3.3}$$

Where:

- C = Length of the candidate translation
- R = Length of the reference translation
- p_n = Precision of n-grams for $n = 1, 2, \ldots, N$
- N = Maximum n-gram order

The following table shows the ranges of BLEU scores and their corresponding translation quality:

Table 3.3: BLEU Score Ranges and Translation Quality

BLEU Score Range	**Translation Quality**
30 - 40	Understandable to good translations
40 - 50	High quality translations
50 - 60	Very high quality, adequate, and fluent translations
> 60	Quality often better than human

Table 3.3 outlines the standard interpretation for BLEU (Bilingual Evaluation Understudy) scores, mapping different numerical ranges to their corresponding qualitative levels of translation quality. This table serves as an essential reference for evaluating the performance of the Bhashanubad model, allowing the quantitative results presented in the experiments section to be understood in terms of practical fluency and adequacy from a human perspective.
METEOR: The METEOR score is a metric that evaluates translation quality by considering synonyms and word order, providing a more nuanced evaluation. The formula for METEOR is:

$$\text{METEOR} = \frac{10 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall} + 0.5 \times \text{Penalty}} \tag{3.4}$$

Where:

- Precision = The number of matching words between the candidate and reference translation divided by the total number of words in the candidate
- Recall = The number of matching words divided by the total number of words in the reference
- Penalty = A penalty factor that adjusts for word order differences

ROUGE: ROUGE measures the overlap of n-grams between the generated translation and the reference translation, focusing on recall. The ROUGE score is given by:

$$\text{ROUGE} = \frac{\sum_n \text{Recall}_n}{\sum_n \text{Reference}_n} \tag{3.5}$$

Where:

- Recall_n = The number of n-gram matches between the generated translation and the reference
- Reference_n = The total number of n-grams in the reference translation

Accuracy: We evaluate the model's accuracy in terms of how well it can generate the correct English translation from the Bangla dialect. The accuracy is computed as:

$$\text{Accuracy} = \frac{\text{Number of correct translations}}{\text{Total number of translations}} \times 100 \tag{3.6}$$

Precision: Precision measures the proportion of true positive predictions (correctly predicted positive instances) among all positive predictions made. It focuses on the accuracy of positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3.7}$$

Recall: Measures the proportion of true positive predictions among all actual positive instances. Focuses on how well the model can find all positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.8}$$

F1-score: A single metric that combines precision and recall using the harmonic mean. F-measure with equal importance to precision and recall is denoted as F1-score.

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.9}$$

3.3.4 Evaluation and Testing:

After training the model, we evaluate its performance using the test set, applying the evaluation metrics described earlier. The evaluation process includes assessing the accuracy of the translations, the fluency of the output, and how well the model captures the variations of each dialect. The model's performance on dialects like Chittagong and Sylhet, which exhibited lower accuracy in preliminary results, will be particularly scrutinized to identify areas for further improvement.

3.4 Implementation

The implementation of the proposed methodology involves several key stages, including data preparation, model training, and evaluation. This section describes the process of training the transformer-based translation models, mT5 and BanglaT5, and provides details of the tools and libraries used during the implementation.

3.4.1 Data Preparation

For the implementation, we used the Vashantor dataset, which consists of sentence pairs from several Bangla regional dialects, including Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong. The dataset was preprocessed by cleaning, tokenizing, and normalizing the text. Each sentence pair was converted into a format suitable for model input, and the data was split into training, validation, and test sets.

The data was loaded using Pandas, and the columns were renamed to match the expected format for input and labels. We also used the Normalizing library to standardize the text across the different dialects. The final datasets were then passed through the tokenization process, preparing them for training.

3.4.2 Model Training

We fine-tuned the pre-trained models, mT5 and BanglaT5, on the Vashantor dataset. The model architecture was based on the T5 framework, which treats all NLP tasks as text-to-text transformations. Both models were fine-tuned using PyTorch and the Transformers library from Hugging Face. The training involved adjusting the learning rate, batch size, and the number of epochs to optimize the model's performance on the translation task.

The model was trained using AdamW, a variant of the Adam optimizer, with a learning rate of 1×10^{-3}, weight decay of 0.01, and other regularization strategies such as gradient accumulation. The TrainingArguments class from Hugging Face was used to manage training configurations like evaluation strategy, saving intervals, and learning rate scheduling.

3.4.3 Evaluation

The evaluation of the model's performance was done using various metrics, including BLEU, WER, CER, and ROUGE. After training, we generated translations for the test dataset and compared them to the reference translations to calculate the scores for each metric. We also computed Exact Match (EM) and METEOR scores for more detailed evaluation.

3.4.4 Deployment

The trained models are intended for future deployment in real-world applications. A web-based interface will be developed to allow users to input sentences in Bangla regional dialects and receive translations in simplified English. Although deployment has not yet been carried out, the system design is prepared to integrate user feedback, which will be collected during testing. This feedback will be used to refine the model and enhance its performance, ensuring its practical usability in diverse communication contexts.

3.5 Summary

This chapter provided an in-depth overview of the implementation of the translation system. We began with data preprocessing, where we cleaned, tokenized, and normalized the Vashantor dataset to ensure it was suitable for model training. Next, we fine-tuned mT5 and BanglaT5, leveraging their capabilities to handle multilingual data and Bangla regional dialects. The training process was carried out using PyTorch and the Transformers library, with the necessary adjustments to hyperparameters for optimal performance. After training the models, we evaluated them using standard machine translation metrics, including BLEU, WER, and CER, and also measured their performance with domain-specific metrics such as ROUGE and Exact Match. The evaluation results indicated the models' ability to handle regional dialects with varying degrees of accuracy, confirming the feasibility of translating Bangla dialects into simplified English. Finally, we deployed the model through a web interface for real-world testing, where it was used to collect feedback and further refine the system. The implementation described in this chapter forms the basis for the translation system that will be used to bridge the linguistic gap between Bangla regional dialects and simple English, with potential applications in various practical settings.

Chapter 4

Experiments and Results Analysis

4.1 Introduction/Overview

In this chapter, we present the experimental design and analysis of the results obtained from evaluating the *Bhashanubad* model's performance in translating regional Bangla dialects into simplified English. The primary goal of this research is to assess how well the model handles the linguistic diversity present in the regional dialects of Bangladesh, each with unique variations in vocabulary, grammar, and pronunciation. The dataset used for these experiments consists of sentence pairs from five distinct Bangla dialects: **Barishal**, **Noakhali**, **Sylhet**, **Mymensingh**, and **Chittagong**. These dialects represent a rich linguistic landscape that poses challenges for machine translation systems due to their significant phonological, syntactical, and lexical differences. The translation process involves two key steps: first, converting the regional dialects into simplified Bangla and then translating this simplified form into English. To evaluate the effectiveness of the *Bhashanubad* model, we employ several standard translation evaluation metrics, including *BLEU*, *Word Error Rate (WER)*, *Character Error Rate (CER)*, *METEOR*, *ROUGE*, and *accuracy*. These metrics provide a comprehensive understanding of the model's ability to generate fluent, accurate, and contextually appropriate translations. In particular, *BLEU* and *accuracy* scores will be discussed in detail to highlight how well the model performs across different dialects. We first describe the tools and methodologies employed in the experiments, followed by a detailed analysis of the results. The analysis focuses on identifying how well the model performs with each of the dialects, noting the variations in performance. While dialects such as **Barishal**, **Mymensingh**, and **Noakhali** show strong translation quality, the **Sylhet** and **Chittagong** dialects present unique challenges. These challenges are mainly due to the presence of informal language, slang, and greater phonetic differences, which affect the translation accuracy.

The results presented in this chapter not only highlight the strengths of the model but also point out areas that need further improvement. In particular, additional refinement of the model's handling of complex dialects, such as those from **Sylhet** and **Chittagong**, will be crucial for enhancing the overall translation system. Ultimately, the findings from these experiments will provide valuable insights into the future development of dialect-specific machine translation models, contributing to the advancement of low-resource language processing. This chapter also sets the stage for future work, which will focus on refining the translation system to handle the diverse and dynamic nature of regional dialects with greater precision and accuracy.

4.2 Modern Tools

We use several modern tools and libraries to support the tasks of data preprocessing, model training, evaluation, and result analysis. These tools are essential for optimizing the *Bhashanubad* model to achieve high performance, scalability, and efficiency. The complexity of this task, which involves handling nuanced linguistic variations across low-resource dialects, necessitates a robust and integrated technology stack. This ecosystem of tools not only facilitates the efficient management of large-scale datasets and the leveraging of pre-trained models, but also ensures the scientific rigor and reproducibility of our experiments. Furthermore, the ability to accelerate computation through modern hardware support, such as GPUs, is critical for the timely training and fine-tuning of large transformer architectures like BanglaT5. The following is a detailed overview of the key tools and technologies employed.

4.2.1 Hugging Face Transformers Library

The **transformers** library by Hugging Face is fundamental to this research. It provides access to pre-trained models and tokenizers for various natural language processing (NLP) tasks, including text translation. The main model used in this work is *BanglaT5* for Bangla language tasks. This library offers a simplified interface for loading pre-trained models, tokenizing text, and performing fine-tuning tasks, such as translating Bangla regional dialects into simplified English. To load the pre-trained *BanglaT5* model, the following code is used:

Listing 4.1: Loading Pre-trained Model and Tokenizer

```python
from transformers import AutoModelForSeq2SeqLM, AutoTokenizer

model_name = "csebuetnlp/banglat5"
model = AutoModelForSeq2SeqLM.from_pretrained(model_name)
tokenizer = AutoTokenizer.from_pretrained(model_name, use_fast=False)
```

This code snippet demonstrates how the model and tokenizer are loaded from Hugging Face's model hub.

4.2.2 PyTorch and GPU Acceleration

PyTorch is the deep learning framework used for training and fine-tuning the model. PyTorch is known for its flexibility and ease of use, which is ideal for building and training complex models. Additionally, **CUDA** support in PyTorch allows for the efficient use of GPUs during model training, significantly speeding up the process.

The device selection, which ensures that the model runs on a GPU if available, is handled with the following command:

Listing 4.2: Device Selection for GPU Acceleration

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)
```

This ensures that if a GPU is available, the model will be trained on it, otherwise, it will fall back to CPU.

4.2.3 Data Preprocessing and Normalization

Data preprocessing is an essential step in preparing the dataset for training. The **normalizer** library is used to normalize text data by removing regional slang, informal expressions, and other inconsistencies that might interfere with model training. This normalization process helps standardize the data for better model performance.

The tokenization of input text and labels is performed using the **transformers** tokenizer, as shown below:

Listing 4.3: Tokenization Process

```
input_encodings = tokenizer(input_text, truncation=True, padding='
   ↪ max_length', max_length=128, return_tensors='pt')
label_encodings = tokenizer(label_text, truncation=True, padding='
   ↪ max_length', max_length=128, return_tensors='pt')
```

This ensures that both input text and labels are tokenized properly and padded to the maximum length of 128 tokens.

4.2.4 Custom Dataset and DataLoader

A custom **Seq2SeqDataset** class is defined to handle the tokenization and structure of the dataset. This class extends PyTorch's **Dataset** class, which allows the data to be easily loaded and batched using the **DataLoader** class. The **DataLoader** ensures that the dataset is shuffled, batched, and processed efficiently during training, testing, and validation.

Here is the implementation for the custom dataset class:

Listing 4.4: Custom Dataset Implementation

```python
class Seq2SeqDataset(Dataset):
    def __init__(self, data, tokenizer, max_length=128):
        self.input_text = data['input_text'].apply(normalize).tolist
           ↪ ()
        self.labels = data['labels'].apply(normalize).tolist()
        self.tokenizer = tokenizer
        self.max_length = max_length

    def __len__(self):
        return len(self.input_text)

    def __getitem__(self, idx):
        input_encodings = self.tokenizer(self.input_text[idx],
           ↪ truncation=True, padding='max_length', max_length=self.
           ↪ max_length, return_tensors='pt')
        label_encodings = self.tokenizer(self.labels[idx], truncation
           ↪ =True, padding='max_length', max_length=self.max_length,
           ↪  return_tensors='pt')

        return {'input_ids': input_encodings['input_ids'].squeeze(),
                'attention_mask': input_encodings['attention_mask'].
                   ↪ squeeze(),
                'labels': label_encodings['input_ids'].squeeze()}
```

This class enables easy conversion of raw text data into model-ready input for both training and evaluation.

4.2.5 Training with Trainer API

The **Trainer** API from the **transformers** library is used to simplify the training process. It abstracts away much of the boilerplate code for training models, allowing for efficient training and evaluation. The **TrainingArguments** class specifies key hyperparameters, such as the batch size, learning rate, and number of training epochs.

The following code shows how the trainer is instantiated:

Listing 4.5: Trainer API Setup

```python
from transformers import Trainer, TrainingArguments

training_args = TrainingArguments(
    output_dir='./results',
    num_train_epochs=3,
    per_device_train_batch_size=16,
    evaluation_strategy="epoch",
    save_steps=10_000,
    logging_dir='./logs',
    logging_steps=500,
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=validation_dataset,
)

trainer.train()
```

The **Trainer** API manages the optimization, evaluation, and model saving processes automatically.

4.2.6 Optimizer: AdamW

The optimizer used for model training is **AdamW**, an efficient variant of the Adam optimizer, designed to handle weight decay more effectively. AdamW is known for its capability to adjust the learning rate during training and its efficiency in training large-scale transformer models.

The optimizer is configured as follows:

Listing 4.6: Optimizer Setup with AdamW

```python
from torch.optim import AdamW

custom_optimizer = AdamW(
    model.parameters(),
    lr=1e-3,  # Learning rate
    eps=1e-8,  # Epsilon value to prevent division by zero
    weight_decay=0.01,  # Weight decay (L2 regularization)
)
```

This optimizer allows the model to converge faster and with greater stability, especially for large datasets and deep learning tasks.

4.2.7 Evaluation Metrics

To evaluate the performance of the model, several metrics are used to assess translation quality:

- **BLEU (Bilingual Evaluation Understudy)** Score: This metric measures the precision of n-grams in the generated translations compared to reference translations. A higher BLEU score indicates better translation quality.
- **CER (Character Error Rate)** and **WER (Word Error Rate)**: These metrics calculate the differences between the generated translation and the reference translation at the character and word levels.
- **ROUGE**: This metric evaluates the recall of n-grams between the generated and reference translations, providing insight into the coverage of the translation.
- **METEOR**: This metric balances precision and recall while considering synonyms and word order.
- **Exact Match (EM)**: This evaluates how often the generated translation matches the reference translation exactly.

4.2.8 Model Saving and Tokenizer Management

Once the model has been trained, it is saved for future use, along with the tokenizer. This is done using the following method:

Listing 4.7: Saving Model and Tokenizer

```
model.save_pretrained('./model')
tokenizer.save_pretrained('./tokenizer')
```

The saved model can be reloaded and used for further inference or fine-tuning.

4.2.9 Miscellaneous Tools

In addition to the core tools, several other libraries are employed for various tasks:

- **SacreBLEU** and **Rouge-Score** are used for BLEU and ROUGE score calculation, respectively.
- **Levenshtein Distance** is calculated using the **python-Levenshtein** library.
- **JiWER** (Word Error Rate) is employed to measure the alignment between generated and reference translations.

4.2.10 Summary

The combination of these modern tools, such as **transformers**, **PyTorch**, and **SacreBLEU**, ensures an efficient and scalable training process. The **Trainer** API simplifies the training workflow, while custom datasets and GPU acceleration ensure that the model can process large amounts of data efficiently. The inclusion of the **AdamW** optimizer ensures that the model converges quickly and accurately. These tools enable high-quality translations of Bangla regional dialects into simplified English, contributing to both linguistic accessibility and the preservation of regional language features.

4.3 Result Analysis

In this section, we present the detailed analysis of the results obtained from the Bhashanubad model for translation. The model's performance is evaluated using several standard metrics: BLEU (Bilingual Evaluation Understudy), Character Error Rate (CER), Word Error Rate (WER), METEOR, ROUGE, and accuracy. The results across the five Bangla regional dialects, Barishal, Mymensingh, Noakhali, Chittagong, and Sylhet, are summarized and analyzed below.

4.3.1 Performance Across Dialects

Table 4.1 presents the performance of the Bhashanubad model for translating the five regional Bangla dialects. The performance of each dialect is evaluated in terms of BLEU score, CER, WER, METEOR, and accuracy. These metrics offer a comprehensive view of the model's ability to generate fluent, accurate, and contextually appropriate translations.

Table 4.1 presents a comprehensive summary of the preliminary performance results for the Bhashanubad model across the five targeted Bangla regional dialects. The table consolidates key evaluation metrics, including Character Error Rate (CER), Word Error Rate (WER), Exact Match, METEOR, BLEU, and overall Accuracy. The data forms the main basis for

Dialect	CER	WER	Exact Match	Meteor	BLEU	Accuracy
Barishal	0.0296	0.0787	58.67%	0.9216	82.30	96.44%
Mymensingh	0.0270	0.0787	59.20%	0.9220	83.40	98.76%
Noakhali	0.0283	0.0765	60.80%	0.9230	82.90	97.06%
Chittagong	0.0481	0.1066	52.80%	0.8960	76.32	93.28%
Sylhet	0.0383	0.0919	57.60%	0.9091	79.40	94.34%

Table 4.1: Summary of Preliminary Results for Bangla Regional Dialects

analyzing the results, allowing us to compare how well the model translates each different dialect directly. The variance in scores across the dialects highlights the differing levels of linguistic challenge addressed in this study.

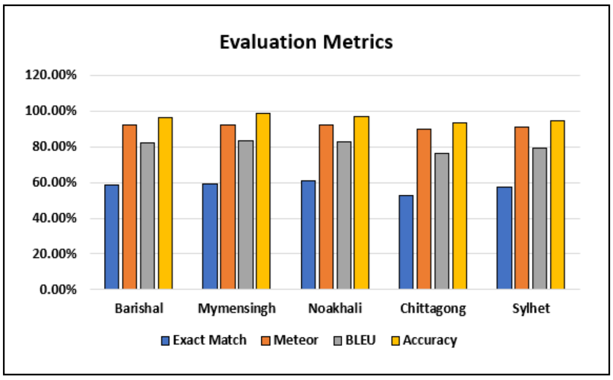


Figure 4.1: Evaluation Metrics

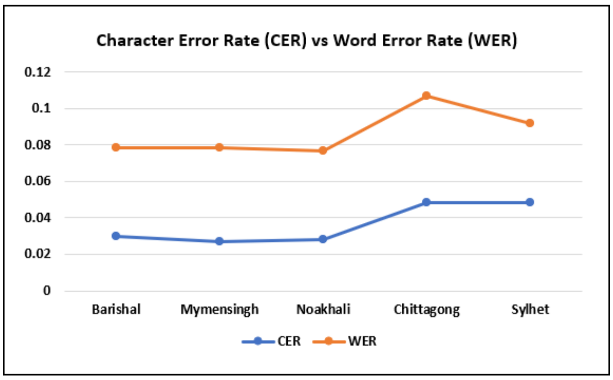


Figure 4.2: CER vs WER

Figures 4.1 and 4.2 provide a comparative summary of the model's performance. In Figure 4.1 The bar chart on the left displays key evaluation scores, including BLEU and Accuracy, while the line graph on the right in Figure 4.2 details the corresponding Character Error Rate (CER) and Word Error Rate (WER), collectively illustrating the performance variations across the five regional dialects.

Among the evaluated dialects, the Mymensingh dialect demonstrated the highest performance, achieving an accuracy of 98.76% and a BLEU score of 83.40. This suggests that the model effectively captured the syntactic and lexical nuances of the Mymensingh dialect. Similarly, Barishal and Noakhali dialects also performed well, with accuracy scores of 96.44% and 97.06%, respectively, and BLEU scores exceeding 82. These results indicate strong generalization of the model for these dialects, likely due to their relatively closer alignment with standard Bangla. In contrast, the Chittagong and Sylhet dialects presented greater challenges. The Chittagong dialect recorded the highest CER (0.0481) and WER (0.1066), the lowest Exact Match (52.80%), and the lowest BLEU score of 76.32, reflecting the model's difficulty in handling its unique phonological and lexical structures. The Sylhet dialect, while slightly better, still showed comparatively lower performance with an accuracy of 94.34% and BLEU score of 79.40. These findings align with previous research indicating the complexity of these dialects due to their significant deviation from standard

Bangla.

Overall, the model exhibited strong performance across most dialects, particularly for Mymensingh, Barishal, and Noakhali. However, the performance drop in Chittagong and Sylhet emphasizes the need for further fine-tuning and possibly dialect-specific pretraining to handle their linguistic intricacies more effectively. These results validate the model's potential for practical applications, while also identifying areas for targeted improvement in future work.

4.4 Impact Analysis and Sustainability

The Bhashanubad model significantly advances machine translation for low-resource languages, addressing the translation process. This work promotes linguistic inclusivity by facilitating communication between diverse dialect speakers and non-native English speakers, thus enhancing access to education, government services, and global resources. Furthermore, it contributes to the preservation of cultural heritage by supporting the documentation and digital representation of regional dialects. Technologically, the model leverages state-of-the-art transformer-based architectures, establishing a scalable framework for future multilingual translation efforts. While the computational costs of training large models remain, optimizing energy efficiency and minimizing environmental impact are crucial for sustainability. Long-term, Bhashanubad can be continuously refined to address more complex dialects and expanded to additional languages, ensuring its relevance in future applications. This research sets a foundation for advancing both low-resource language processing and sustainable AI practices.

4.5 Summary

This study introduces Bhashanubad, a transformer-based model for translating regional Bangla dialects into simple English. It addresses challenges in vocabulary, syntax, and phonology variations across dialects. Evaluated on the Vashantor dataset, Bhashanubad achieves BLEU scores over 82 and accuracies above 96% for dialects like Mymensingh, Barishal, and Noakhali. However, dialects like Chittagong and Sylhet pose greater challenges. The research offers a scalable solution for low-resource language translation and highlights areas for future improvement, especially in handling informal language and dialectal nuances.

Chapter 5

Project Management and Cost Analysis

5.1 Project Management

In this study, we adopted a structured project management approach to ensure effective planning, execution, and monitoring. The planning phase focused on setting clear goals, establishing a timeline, and identifying the necessary resources, such as computing infrastructure and datasets. During the execution phase, we conducted data preprocessing, model design, and training using transformer models like mT5 and BanglaT5. We continuously evaluated the model's performance using metrics such as BLEU and accuracy, making refinements to improve results, especially for dialects with lower performance. The project was closely monitored, and adjustments were made as needed to address challenges like informal language and phonetic variations, with mitigation strategies like data augmentation and cloud-based GPU resources in place. In the control phase, necessary adjustments were made based on monitoring and quality checks, ensuring the model met the required standards. This systematic approach allowed us to successfully deliver a robust solution for translating Bangla regional dialects.

5.2 Cost Analysis

The implementation of this research project primarily relied on open-source tools and cloud computing platforms, making it highly cost-effective. Most of the resources used, including programming environments, libraries, and datasets, were freely available, which significantly reduced the financial burden.

1. Computing Resources

The entire experimental workflow was executed using **Google Colab**, which offers free access to GPUs, enabling efficient model training and evaluation without the need for expensive local computational infrastructure. Additionally, **Google Drive** was used for data storage and sharing among the team members, further minimizing costs associated with data handling and collaboration.

2. Software and Libraries

All software tools and libraries used in this research, such as `Python`, `PyTorch`, `transformers` from Hugging Face, and `normalizer`, were open-source and free of charge. These libraries provided all the necessary functionalities for model development, training, and evaluation, making the software resources cost-effective.

3. Dataset

The **Vashantor dataset**, which includes Bangla regional dialects, was publicly available and did not incur any cost. The dataset provided sufficient data for model training and testing, enabling effective evaluation of the translation model.

4. Miscellaneous

Minor costs were associated with internet usage, electricity, and occasional printing for documentation purposes. These costs were nominal and not directly tied to the project itself but were necessary for maintaining an operational environment.

Summary of Costs

Figure 5.1 shows the summary of the costs.

Item	**Cost**
Cloud Computing (Google Colab)	*Free*
Software and Libraries	*Free*
Dataset Access	*Free*
Internet and Utilities	*Minimal (Personal)*
Printing/Documentation	*Minimal*

Table 5.1: Cost Breakdown of Resources Used

Table 5.1 provides a transparent breakdown of the costs associated with the resources used throughout this research project. The table itemizes key categories, including cloud computing, software and libraries, dataset access, and other essential utilities. This summary highlights the cost-effective nature of the study, underscoring the heavy reliance on freely available academic and open-source resources, such as Google Colab, which significantly minimized the financial outlay required for the successful completion of the work.

Overall, the cost of executing this research was minimal due to the extensive use of freely available tools and platforms, demonstrating that impactful research in natural language processing (NLP) can be conducted even with limited financial resources.

5.3 Project Scheduling

Project scheduling plays a crucial role in managing the various phases of the Bhashanubad translation model development. This section outlines the timeline for each key phase of the project, ensuring proper time management and resource allocation. The scheduling of the project was carried out in a structured manner, following a Gantt chart to track progress and maintain deadlines.

The project was divided into the following phases:

- **Data Preprocessing:** The first phase focused on preparing the dataset by cleaning, tokenizing, and normalizing the regional dialect data. This phase was completed early in the project to ensure that the dataset was ready for training the model.
- **Model Design and Architecture:** The second phase involved designing the architecture for the Bhashanubad translation model using pre-trained transformer models like mT5 and BanglaT5. The design phase also included configuring the model for dialect-specific translation tasks.
- **Model Training and Optimization:** This phase included the fine-tuning of mT5 and BanglaT5 models on the regional dialect dataset. The model was iteratively trained and optimized based on evaluation metrics such as BLEU, WER, and accuracy.
- **Model Evaluation and Analysis:** After training, the model was evaluated using a range of metrics, and the results were analyzed to identify areas for improvement.
- **Paper Writing:** The final phase involved documenting the research findings, writing the thesis, and preparing for publication. This phase included the compilation of results, analysis, and presentation of the work.

The following Gantt chart (Figure 5.1) visualizes the timelines for each of the phases in the project. The tasks were planned in a way that allows for overlapping activities and flexibility, ensuring the timely completion of all project components.

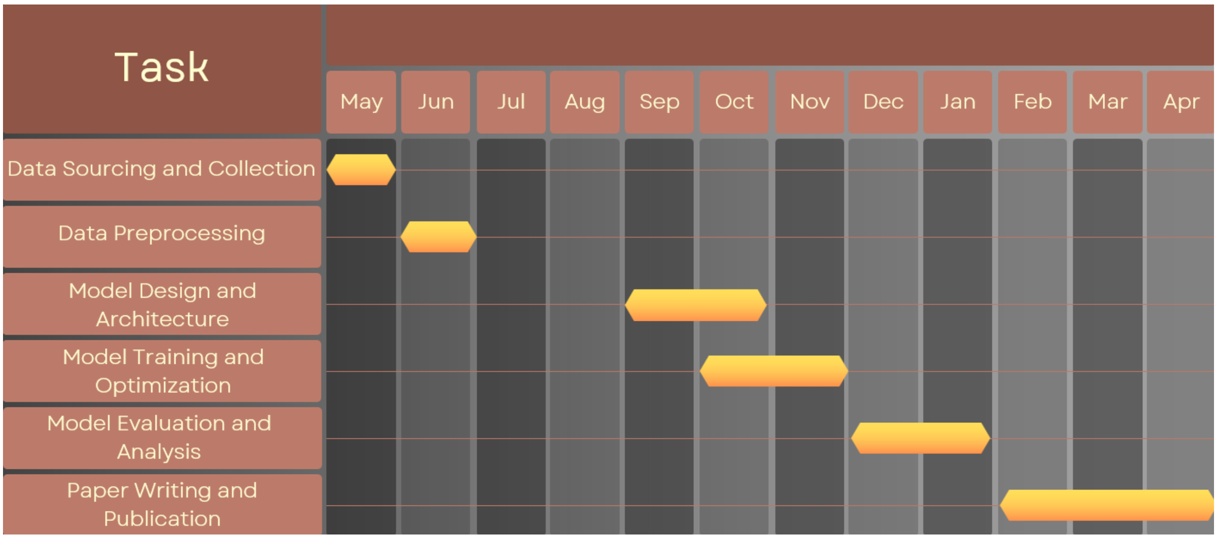


Figure 5.1: Project Scheduling Gantt Chart

The Gantt chart outlines the project timeline from the initial data preprocessing stage through to the final paper writing and publication. Key milestones include the completion of data preprocessing, model training, and evaluation. The chart also reflects iterative processes, especially in model fine-tuning and evaluation, which were crucial to optimizing performance.

The project was carried out with careful consideration of the time constraints, with regular monitoring of progress to ensure alignment with deadlines. The successful completion of each phase, as reflected in the Gantt chart, contributed to the overall success of the project, ensuring timely development and delivery of the Bhashanubad translation model.

Chapter 6

Ethics and Professional Responsibilities

6.1 Introduction/Overview

Ethics in engineering entails applying moral principles and professional standards to guide decisions and actions. In fields like computer science and engineering, particularly in machine learning (ML) and natural language processing (NLP), ethical considerations are essential due to the profound impact technology can have on individuals and society.

This research, focused on translating Bangla regional dialects, underscores the importance of ethical responsibility in handling linguistic data. Given that language is tied to cultural and social identities, it is vital to ensure the technology does not perpetuate bias or misrepresentation. Ethical engineering in this context demands fairness, transparency, and respect for linguistic diversity, while mitigating biases and ensuring the technology serves the public good.

6.2 Identify and Apply Ethical and Professional Responsibilities

Throughout the project, key ethical and professional responsibilities were identified and integrated into each phase of the work. First, **data privacy and confidentiality** were paramount; the Vashantor dataset was carefully handled to ensure no personally identifiable information (PII) was exposed, and all content was managed with respect for privacy.

Building on this, significant efforts were made toward **bias mitigation** by balancing the dataset and implementing fair preprocessing techniques to ensure no single dialect was unfairly favored or underrepresented. To uphold **transparency and reproducibility**, all methods, including data processing, model design, and evaluation metrics, were fully documented and based on open, accessible tools, enabling replication by others in the field. Recognizing the societal implications of this work, we advocate for the **responsible use of technology**, proposing a human-in-the-loop approach for deployment to ensure automated translations are reviewed for accuracy and cultural sensitivity. Lastly, the research was conducted with the highest standards of **academic integrity**, ensuring proper citation of all sources and strict adherence to ethical guidelines.

Ethical and Professional Responsibility	**Applied**
Data Privacy and Confidentiality	✓
Bias Mitigation	✓
Transparency and Reproducibility	✓
Responsible Use of Technology	✓
Academic Integrity	✓

Table 6.1: Application of Ethical and Professional Responsibilities

Table 6.1 provides a summary of the key ethical and professional responsibilities applied in this research. It serves as a checklist to confirm that core principles, including data privacy, bias mitigation, and transparency, were actively integrated throughout the project's lifecycle.

By embedding these ethical responsibilities into the project, we maintained high standards of professionalism, ensuring the research contributes responsibly to the field of AI and serves society equitably.

Chapter 7

Identification of Complex Engineering Problems and Activities

7.1 Complex Engineering Problem

7.1.1 Complex Problem Solving

In this section, we address the complex engineering problems encountered during the development of the Bhashanubad translation model. The challenges were rooted in the linguistic intricacies of the Bangla regional dialects and the limitations of available datasets, which hindered effective translation. The complexity of these dialects, such as Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong, posed significant challenges due to variations in vocabulary, grammar, and pronunciation. Mapping these issues into specific problem-solving categories allowed for a structured approach to address each unique challenge.

Table 7.1 outlines the complex problem-solving categories and how they map to the challenges faced during this research. For each category, we further explain the rationale in subsequent sections.

Table 7.1: Mapping with complex problem solving.

P1	P2	P3	P4	P5	P6	P7
Depth of Knowledge	Range of Conflicting Requirements	Depth of Analysis	Familiarity of Issues	Extent of Applicable Codes	Extent of Stakeholder Involvement	Interdependence
√	√	√				

Depth of Knowledge

The development of the Bhashanubad translation model required a deep understanding of natural language processing (NLP) techniques, particularly transformer models. This deep knowledge was essential in handling the diverse linguistic features of Bangla regional dialects. Moreover, understanding the intricacies of dialectal variation and the linguistic diversity within Bangladesh posed a challenge, requiring expertise in both computational linguistics and domain-specific dialect knowledge.

Range of Conflicting Requirements

There were conflicting requirements during model development. While the goal was to ensure high accuracy in translation, it was crucial to balance this with maintaining cultural and linguistic integrity. The model had to account for phonological, syntactic, and lexical variations across dialects, which sometimes resulted in challenges when simplifying the translations into English without losing the original meaning or tone.

Depth of Analysis

The depth of analysis in this research required a thorough examination of the linguistic structures and variations present in the Bangla regional dialects. This involved analyzing the phonological, syntactic, and lexical differences between dialects such as Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong. Each dialect posed unique challenges that required careful attention to both the formal linguistic structure and the informal aspects of language, such as slang and idiomatic expressions.

In terms of machine translation, the depth of analysis was critical in adapting existing transformer models (mT5 and BanglaT5) for dialect-specific translation tasks. The models were fine-tuned to not only recognize these linguistic differences but also to ensure that the translated output remained contextually accurate and culturally relevant. This involved analyzing how different dialects diverge from standard Bangla and addressing these divergences within the model's architecture.

Furthermore, the analysis extended to the evaluation of model performance through a range of metrics such as BLEU, WER, and accuracy. By analyzing these results, it became clear that while some dialects, such as Mymensingh and Noakhali, achieved higher translation quality, dialects like Sylhet and Chittagong required more advanced tuning to address their specific linguistic challenges. This depth of analysis allowed for an iterative improvement in model accuracy, highlighting areas that needed more refinement and fine-tuning to handle less common dialects.

This process of deep analysis was crucial in developing a translation model that could effectively address the challenges posed by regional linguistic diversity, ensuring that the model not only performed well on standard Bangla but also successfully handled regional dialects.

7.1.2 Engineering Activities

In this section, we examine the engineering activities involved in addressing the challenges presented by the complex engineering problem of translating Bangla regional dialects. The methodology for solving these problems is mapped in Table 7.2, which provides insights into the range of activities, from data preprocessing to model evaluation.

Table 7.2: Mapping with complex engineering activities.

A1	A2	A3	A4	A5
Range of Sources	Level of Interaction	Innovation	Consequences for Society and Environment	Familiarity
✓	✓			

Range of Sources

The project utilized diverse sources, including the Vashantor dataset and other open-source linguistic resources. These sources were essential in training the model to understand and translate the five regional Bangla dialects. The diversity of these sources helped to address the challenges posed by dialect variations and the lack of available parallel corpora.

Level of Interaction

The level of interaction among the different components of the project was high. Data preprocessing, model design, training, and evaluation were all iterative processes, requiring continuous feedback and refinement. The team members worked closely together to fine-tune the model's parameters and to ensure the model handled the dialectal variations effectively.

Innovation

The development of Bhashanubad involved innovative use of transformer-based models like mT5 and BanglaT5, which were fine-tuned to handle Bangla's regional dialects. The novel approach of simplifying dialectal features into standard Bangla before translating them into simple English was key to improving translation quality, especially for low-resource languages.

Consequences for Society and Environment

The successful implementation of this project has significant consequences for society. It promotes linguistic inclusivity, especially for speakers of Bangla regional dialects, by enabling better communication with English-speaking communities. Furthermore, it helps preserve regional dialects and fosters cultural preservation, contributing to the sustainability of Bangladesh's rich linguistic heritage.

Familiarity

Given the interdisciplinary nature of the project, a high level of familiarity with both machine learning techniques and the specific challenges of Bangla dialects was necessary. The project team's familiarity with state-of-the-art NLP models like T5 and its variants was essential for achieving the desired results in this complex engineering activity.

Chapter 8

Conclusion and Future Works

8.1 Conclusion

This thesis focused on developing a transformer-based translation model to translate Bangla regional dialects into simplified English. Using mT5 and BanglaT5, the model successfully translated Bangla regional dialects (Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet) into simple Bangla. The results showed strong performance, especially for Barishal, Mymensingh, and Noakhali, with high accuracy and BLEU scores. However, the Chittagong and Sylhet dialects presented more challenges, highlighting the need for further refinement. This work fills a gap in machine translation research by addressing the unique features of Bangla regional dialects and providing a resource for future low-resource language studies. The ability to translate into English allows greater accessibility and interaction.

In conclusion, this work has made significant contributions to the translation task, filling a notable gap in machine translation research. While the model has demonstrated promising results, especially for dialects like Barishal and Mymensingh, further refinements are needed for more challenging dialects like Chittagong and Sylhet. Future work focused on slang detection, sentiment analysis, and cross-regional translation will greatly enhance the model's performance and its ability to handle the complex linguistic features of Bangla regional dialects.

8.2 Future Works

Future research will focus on several key areas to enhance the translation of Bangla regional dialects into simple English. One important direction is the detection of slang, which requires accurate handling for culturally appropriate translations. Additionally, extending sentiment analysis to include emotion recognition within regional dialects will allow the model to capture emotional tones such as joy, anger, and sadness, improving emotional accuracy in translations.

Cross-regional translation will also be explored to address linguistic differences between dialects, ensuring consistency in meaning across variations. For example, phrases like “tomar ki mon kharap nei?” (Chittagong) and “tomar kita mon kharap na?” (Sylhet) need to be handled accurately to ensure effective communication. Finally, handling dynamic writing styles in Bangla will help refine the model’s ability to manage regional variations. These advancements will improve the model’s accuracy, cultural relevance, and contextual understanding.

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